Organisational Structure and Performance of Consensus Decisions through Mutual Influences: A Computer Simulation Approach

Vicente Salas-Fumás, Carlos Sáenz-Royo, Álvaro Lozano-Rojo

Abstract

This paper models and simulates the formation of consensus through information sharing and social influences among bounded rational individuals connected through a communication network, who collectively decide whether to adopt a new project, policy or idea (innovation in short) or not. Next we examine the sensitivity of group fallibility in the collective adoption decision and the time spent on reaching consensus to parameters of the model such as the economic value of the innovation, the connectivity and size of the network and the degree of social influences. We find that group consensus decisions reduce the probability of commission errors to negligible values (adopting value-destroying innovations), but the probability of omission errors (rejecting value-creating ones) and the time to reach consensus are sensitive to the exogenous parameters with some trade-offs: higher average connectivity of communication networks increases the likelihood of making omission errors in adoption but reduces the time to reach consensus. The results of this research are relevant to managerial decisions affecting the performance of consensus by mutual influences on decision-making in the expanding production and exchange systems of information-intensive networks of empowered workers.

Keywords: Decisions by consensus, organizational networks, organizational fallibility, organizational innovation adoptions, computer simulations.

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1. Introduction

The study of how the structure of organisations affects their collective performance has a long tradition in the management sciences [1,2]. This paper models the process of consensus formation around the decision about adopting a new project, policy or idea, "innovation" in short, among bounded rational and socially influenced individuals who are connected through a predetermined communication network and examines the sensitivity of the performance of consensus-based decision making to different organizational structures.

The set-up consists of a number of nodes in a communications network[1] with links determining who is connected with whom. A single decision unit, an individual or a group, occupies each node. At a certain point in time, a randomly selected node is perturbed by the irruption of a potential innovation; innovation here means anything that disturbs the status quo of the group, with an attached economic value, if adopted, relative to the value attributed to the status quo. The person in the node can mistakenly evaluate the innovation, following bounded rationality, which means that whether the adoption is supported or not is expressed as a probability that depends on the relative value of the innovation. Individuals in the network are also socially influenced, which means that the formation of their own opinion also depends on the number of people in the reference group that supports or does not support adoption at a given moment in time. If the perturbed node decides to support the adoption, a process starts of information sharing and mutually influencing the members of her reference group, the neighbouring nodes in our case. The influenced neighbours evaluate the information and influences received and adopt a position in a probabilistic way, with the probability again depending on the relative value of the innovation and on the social influences. The iterations continue until the whole set of nodes of the network consensually agrees to adopt the innovation or not.

[1] Networks are defined as nodes representing persons (individual actors), units (groups as actors) and legal entities (organizational actors, mainly firms). Brass et al. [3] present a comprehensive overview of the research on networks and organizations in the management literature. Networks have been also viewed as governance mechanisms for collaboration and exchange, together with hierarchies and markets [4]. In this paper, we adopt a purely structural perspective of a network, that is, nodes connected with communication lines: the network has well-defined boundaries and is managed, meaning that there is an external authority that can decide on the number of nodes, which nodes are part of the network, who is connected with whom and so on. The structural networks considered in the paper, hierarchy, matrix and full networks, are those commonly found in business firms.

The performance of group consensus decisions is measured in terms of group fallibility and the time needed to reach a consensus. Group fallibility is determined by the probability of commission (adopting value-destroying innovations by consensus) and omission errors (rejecting value-creating innovations). The time needed to reach consensus is estimated as the number of iterations required before consensus is reached. The organizational structure includes: the type of communication network (hierarchy, matrix and full network in this case), the size, the number of nodes in the network and the intensity of social influences in terms of the weight given to others' opinions. Superior performance means lower commission and omission errors and shorter time to consensus on adoption for wealth-creating innovations.

The research methodology used to evaluate the performance of consensus-based decision making by mutual influences is agent-based simulation modelling (see [5,6,7,8,9] for reviews of applications of agent-based models (ABMs) in organizational research). The modelled organizational design decisions share the characteristics suitable for the application of ABMs [9]: from individual to group behaviour, the influence of the organizational structure on the collective outcome, and the relevance of out-of-equilibrium results. In particular, the simulation method used in the analysis tries to replicate the process of mutual influences and information sharing, as it is likely to take place in a real organization with bounded rational and socially influenced members. Bounded rationality [10,11] and social influences [12,13] as conditions of individual and group behaviour are at the core of organizational research. What we propose here is a common framework for studying organisations as information-processing mechanisms with bounded rational individuals as building blocks and organisations as socials structures that rely on power and the group culture to influence the members' behaviour [14].

The results confirm that organisational fallibility in consensus decision making, regarding whether to support the adoption of an innovation or not, depends on both the fallibility of individual members and the structure of the organisation, which includes the network structure, the size of the network and the degree of social influences. Consensus decision-making reduces the expected loss of commission errors to practically zero in all communication networks, including networks of reduced size. However, omission errors and the time to reach consensus vary in an economically significant way across communication networks, not always in the same direction. Managers who want to implement a consensus-based decision system will then face a trade-off between, for example, the choice of the hierarchy and the matrix, with fewer omission errors but a long time taken before reaching consensus, and the choice of a full network, with more omission errors but a shorter time to reach consensus.

The consensus-based decision process studied here is an alternative to authority-based decisions in groups [15,16] and close to group decisions under the unanimity rule. Research on performance of group decisions under the unanimity rule focuses in the formation of consensus in committees [17,18], where all the members interact with each other at the same time. This paper is different in that it examines the performance of consensus decision making implemented in communication networks where interactions occur only with neighbours of the corresponding node and the group adjusts gradually towards consensus.

The relevance of studying consensus-based decision-making in collective actions is justified on normative and positive grounds. On the normative side, consensus has the advantage over welfare maximization by a benevolent dictator [17,19] in that it is akin to Pareto optimal outcomes free from interpersonal comparisons of utility. With three or more alternatives to choose from, consensus is also free from the inconsistency of voting by the majority rule [20]. At the organisational level, consensus facilitates coordination, especially when the shared information is tacit, and assures cooperative behaviour by all the agents involved in the implementation of decisions ([21] and the references cited therein). Group consensus is also recommended when taking wrong decisions can imply severe damage to the group [22]. However, consensus has drawbacks too: it may take a long time before it is formed [17,23] and it may reduce the diversity of ideas and experimentation in groups. Research is then needed to investigate the benefits and costs of the kind that we examine in this paper.

On the positive side, the interest in consensus-based decision making by mutual adjustment in groups is increasing today with the expansion of knowledge-based, people-empowered, IT-supported networks of communication and interpersonal relationships among diverse individuals that challenge authority-based decision making. Tacit knowledge is growing in importance in most economic activities, and the decentralisation of decision-making power is almost inevitable; post-bureaucratic control mechanisms rely more and more on corporate norms and on a culture of strong social influences. The proliferation of organisational forms such as cooperatives, partnerships and co-determination, which explicitly renounce hierarchical authority and control, is also evidence of the progressive use of non-hierarchical decision structures.[2] The complex reality embedded in these highly fluid environments recommends simulating it in ABM environments to determine the sensitivity of collective performance to structural variables such as the characteristics of the communication network and the degree of social influences.

Organisational architecture design decisions for the purpose of reducing the fallibility of bounded rational individual decision makers have been investigated before [22,24,25]. The research so far has focused mainly on comparing the performances of group decision making under different methods of allocating decision-making power among group members, hierarchy versus polyarchy for example, but the influence of the communication network and the group social influences on performance have not yet been examined. We concentrate on only one decision-making mechanism, consensus formation, and compare the performances of different communication networks and degrees of social influences.

Other related literature is that on opinion formation in structural networks [31,32,33,34,35,36]. Most of these papers view opinion formation as a zero or one situation in which a value of one

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[2] Miles and Snow [26] and Snow et al. [27] justify the proliferation of networks, viewed as governance mechanisms of clusters of activities coordinated by different means from lines of command, as being better suited to the demanding environment of the time. Diffusion networks, as a hybrid governance structure of markets and hierarchies, started in Japan with the implementation of production organization systems characterized by flatter structures, greater empowerment, intensive training of employees, self-managed teams of workers, lateral exchanges of information and a strong culture of social influences and mutual trust [28]. Firms' investment in information technology further changed the internal organization of firms towards being less authority-based in decision-making [29,30]. Although this paper adopts a structural view of networks, it could also be extended to accommodate networks as institutions with no formal authority, intense information flows and a strong culture.

occurs when the number of people who share the opinion is above a threshold, and zero otherwise. Moreover, the issue demanding an opinion does not have an assigned economic value, so rational behaviour does not enter the analysis. In this paper, the innovation that has to be supported or not has an economic value and the probability of supporting it is a value between zero and one that depends on the relative economic value of the innovation and on the influences of supporters and non-supporters in the reference group.

The remainder of the paper is organised as follows. Section 2 presents a description of organisational structure and the basis of individual behaviour, as well as the dynamics of the processes of information exchange and social influences that lead to consensus formation around the decision on whether to adopt an innovation or not. Section 3 presents the results of the computer simulations in terms of organisational performance along the dimensions of probability that the consensus is on the alternative that is rationally preferred by the organisation and the time needed to reach the consensus. Section 4 contains a discussion of the main results and how they relate to others in organisational research. Finally, the conclusions summarise the main results of the research and suggest future extensions.

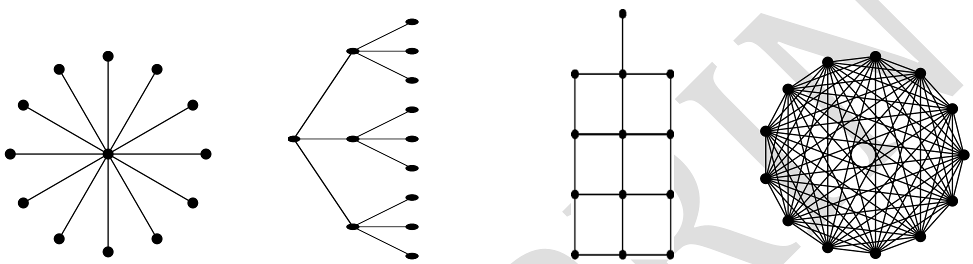
2. Organisational model and research methodology

This section explains in certain detail the main blocks of collective action and decisions (structure, formation of individual opinions, dynamics of influences and performance), together with the ABM simulation that pulls all the elements together.

2.1. Organisational structure

The organisational structure includes the communication network, the decision-making mechanism and the degree of social influences. The communication networks considered are: the *hierarchy* (inverted tree), the *matrix* (lattice) and the *full network*, as summarised in Figures 1 to 3. The hierarchy can adopt two forms, the *star* (Figure 1a), in which there is one central node all the rest are connected to (the span of control of a hierarchy with N nodes is always N-1), and the pure hierarchy (Figure 1b), which contains multiple branching nodes and a varying span of control (three in our case). In the matrix structure, each node has vertical and lateral communication links. In the full network, each node is directly connected to all the other nodes. Networks have different average degrees of *connectivity* (the number of other nodes to which a particular node is directly connected).[3] Each node of the network is an *agent*, which can be a single person or a group (team) behaving as a single decision unit. The communication and mutual influences between the nodes of the network are restricted to nodes that are directly connected (neighbouring nodes). There are no external influences except the innovation that appears randomly in one node of the network.

Figure 1. Communication networks considered in the analysis (N=13)



Star. Hierarchy. Matrix. Full Network.

The *decision-making* mechanism establishes who decides and on what in the network. In authority-based decisions, all the decision power is concentrated on one node and the dispersed information needed to make decisions flows to the node through predetermined communication channels. In the consensus-based mechanism, decisions are made following the unanimity rule: all the nodes in the network must agree on the alternative finally chosen. The unanimity rule or consensus formation may be instrumented through committees or through informal and adaptive mechanisms. In the committee, all the members whose unanimity is required meet, exchange information and opinions and persuade each other until they all unanimously converge to support one of the alternatives [17,37]. Other research has proven the utility of formal decision support

[3] In Figures 1, 2 and 3 above, when there are 13 nodes, the star has a connectivity of 12 for the central node and a connectivity of 1 for the other 12 nodes (average connectivity k=24/13=1.84). In a hierarchy with a span of control equal to 3, the central node has a connectivity of 3, the 3 intermediate nodes a connectivity of 4 and the peripheral nodes a connectivity of 1, for an average connectivity of k=24/13=1.84. In the matrix form, there is 1 node with connectivity of 1, 3 with connectivity of 4, 5 with connectivity of 3 and 4 with connectivity of 2 (average connectivity of k=36/13 = 2.8). Finally, in the full network, the connectivity is equal to 12 for each of the 13 nodes.

systems, DSSs, in groups' decisions, without consensus [18,38,39] or with consensus [23]. In consensus formation in committees, the group members all interact with the others at the same time. In the set-up modelled in this paper, consensus takes place gradually, as the outcome evolving from mutual influences among the individuals belonging to an influence group.

The third element of the organisational structure is the degree of *social* influences, which will be a reflection of the group *culture* [40]. This paper uses a manifestation of culture similar to that common in models of opinion formation [41,42], in which individuals respond to the opinion of others through social influences (all the people in the group of reference have equal possibilities of interacting with the others) or through homophily, when interactions are more intense among members with greater affinity.

2.3 Formation of individual opinions

At a certain point in time, in a randomly selected node, a discovery is made of a project, policy or idea that, if collectively adopted, will produce a collective economic value, R^+, which is higher or lower than the value in the status quo, R. The discovery may be the result of on-the-job/node experimentation or external observation. Next, the node that makes the discovery randomly decides to initiate a process of information sharing with members of the neighbourhood in an attempt to convince them to support the innovation. One member of the influence group of member/node j exposed to the innovation will form his or her own opinion about supporting the innovation or not considering the relative economic value of the innovation, R^+/R, and the social influences from the opinions of the neighbours, as indicated below.

Formally, let $I=\{1, 2,\ldots, N\}$ be the number of nodes in a given organisational structure. For each j in I, there is at least one i also in I with which it is connected; we define a binary variable with the value $g(j, i)=1$ when j and i are linked directly by a line from the organisational structure and $g(j, i)=0$ when j and i are not directly linked. The organisation chart is defined by the connections between the nodes/individuals in the organisation: $G=\{g(j, i)|\ j, i \text{ in } I\}$. We define the group of influence on node j as the set of all nodes/individuals who are directly linked: $H^j=\{i \text{ in } I \text{ such that } g(j, i)=1\}$.

Let A={j in I; R} be the subset of those who are not convinced about the change and maintain their preference for the status quo and B={j in I; R^+} be the subset of those who are quite convinced about the superiority of the change and show their support for it. The number of nodes/individuals in subsets A and B will change over time, as explained below. a_t is defined as the number of nodes/individuals who belong to set A in iteration t and b_t as the number belonging to set B. Since the direct relationships between nodes/individuals are limited to those who form part of a group of influence, subsets A and B should be defined at the intersection of each node j. Thus, in the zone of influence H^j of Agent j in iteration t there will be $a_t^j = \# H^j \cap a_t$ individuals in favour of maintaining the status quo and $b_t^j = \# H^j \cap b_t$ in favour of change.

Consider connected nodes j and i, of which node j is initially supportive of the adoption of the innovation, while node i is initially in favour of the status quo. The probability that in iteration t node j will convince node i to shift from supporting the status quo to supporting innovation is given by:

$$p_t^{j,i} = \frac{\left(1+\delta b_t^j\right)R^+}{\left(1+\delta a_t^i\right)R + \left(1+\delta b_t^j\right)R^+} \qquad (1)$$

The complement 1- $p_t^{j,i}$ is the probability that individual j, who is in favour of innovation, will change his or her opinion and support the status quo.

Equation (1) expresses how bounded rationality and social influences intervene in the formation of opinions in favour of adopting the innovation. The probability increases with the relative economic value of the innovation, R^+/R, consistent with the hypothesis of intended rationality: an individual can commit commission and omission errors when making a decision on whether to support the innovation or not, but the probability of committing these errors decreases with the relative value of the innovation (the probability in (1) tends to one as the ratio R^+/R tends to infinity).[4] Parameters a^i_t and b^j_t are, respectively, the number of individuals in the groups of

[4] Centola and Macy [43] refer to the mechanisms of complex contagion that may explain why the response of individuals to the adoption decision may be probabilistic: strategic complements (one innovation rarely appears in

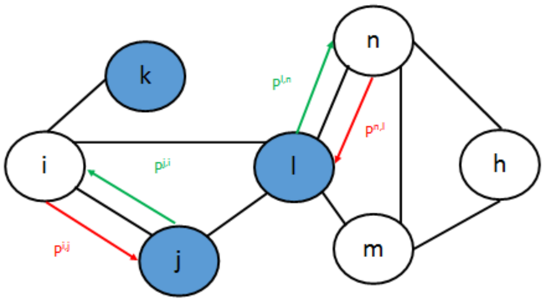
influence in favour of adopting the innovation and in favour of the status quo in iteration *t*. δ is a non-negative parameter that measures the degree of social influences so that higher values of the parameter imply that the opinion of others has more influence on the formation of an individual's own opinion. At time zero, when the perturbation occurs, all the group members support the status quo by default. Therefore, at this point, b_0=0 and a^i_0=the number of neighbours. The larger the connectivity of node *i*, the lower will be the probability that the innovation will have a supporter in the first round and the lower also will be the possibility of passing to the next round. Equation (1) reflects a kind of group culture in which the numbers of neighbouring supporters and non-supporters are equally weighted. The extension to people in the network with different values of δ is straightforward.

2.4. Dynamics of influence

Figure 2 represents what takes place in an iteration of the process towards consensus in a hypothetical network or part of a larger one. In period *t*, nodes *j*, *k* and *l*, in blue, support innovation and nodes *h*, *i*, *m* and *n*, in white, support the status quo. The black lines indicate that the connected nodes can communicate. A red and a green line mean that the connected nodes are exchanging information and influences. Thus, in period *t*, node *j* (*i*) is trying to convince node *i* (*j*) to support the status quo (adoption); the interaction of node *l* with node *n* is similar. Node *h* will be inactive at *t* because all the neighbouring nodes share the same opinion. Nodes *k* and *m* could be active at *t* but they are not because the respective neighbouring candidates to participate in the interaction are already interacting with other neighbours. The probability on a green line is the probability that a node will change from supporting the status quo to supporting the adoption of the innovation; the probability on a red line indicates the probability of changing from supporting the adoption to supporting the status quo.

Figure 2. Interactions among nodes of the network in the process towards consensus formation

isolation), credibility (which increases with the number of previous adopters), legitimacy (given by the position towards the adoption by close friends) and emotional contagion (through symbolic impulses).



If the outcome of the first iteration is such that the two interlocutors coincide on a favourable opinion towards adoption, a new iteration begins with the two in favour of adoption, each interacting simultaneously with one individual in the respective group of influence. Once the cycle is complete, everyone has been persuaded in favour of one option or the other. In the final consensus, the process ends with either a success, if the consensus is in favour of adopting a value-creating innovation or rejecting a value-destroying one, or a failure, if a value-creating (destroying) innovation is rejected (accepted). In the case of disagreements in iteration *t*, a new iteration begins, as many times as required. Mathematically, this process works as a Markov chain, the state space of which is all the possible configurations of interactions of individuals in favour of and individuals opposed to the adoption. Since the networks considered here are connected and non-directed, there are only two absorbing states: either all the members are in favour of adoption or all the members are in favour of maintaining the status quo (with the rest being transient states). The transition probabilities from one state to the other are calculated using the Monte Carlo technique.

2.4. Organisational performance

The interest of this paper is in tracing the individual fallibility of bounded rational individuals, using a measure of organisational fallibility attributed to consensus-based collective decision making, and examining how organisational fallibility varies with the value of the innovation and with the elements of the organisational structure. The fallibility of group decision making by consensus will be expressed in terms of the probability that the consensus will be in favour of adoption of an innovation that should be rejected, $R^{+}<R$, that is, a commission error, and the

probability that the consensus will be to reject an innovation that should be adopted, $R^{+}>R$, that is, an omission error.

The time to reach consensus has economic relevance because a longer time reduces the present value of the innovation being adopted. Therefore, in terms of performance, not only does the probability that a value-creating innovation will be adopted matter, but also the time needed to reach the consensus. We measure the number of iterations to reach consensus as a measure of the time spent on the process as well as the time-discounted probability of reaching consensus on adoption, $e^{-rT}P$, where P is the probability of reaching consensus on adoption, T is the time proxy variable and r is the interest rate.

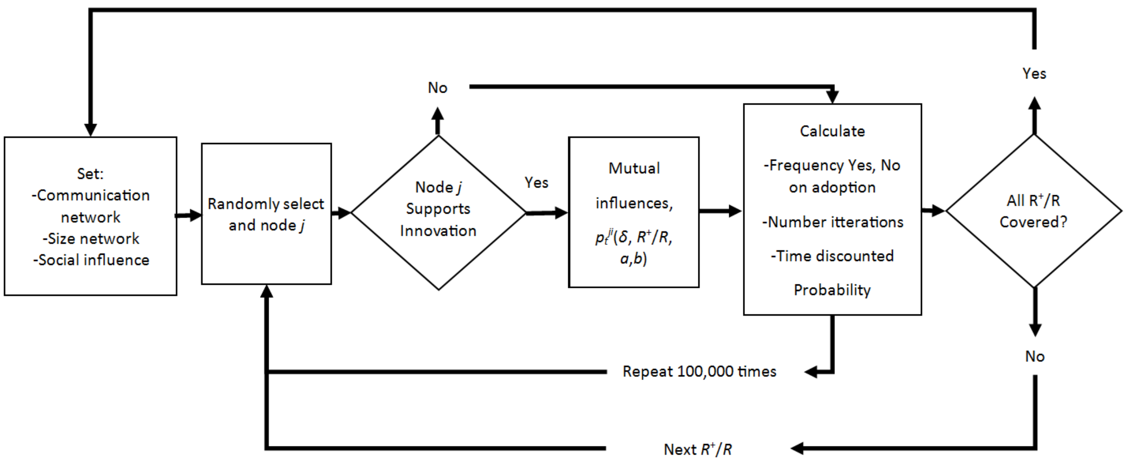
2.5 The ABM methodology

The set-up of consensus formation in communication networks in which nodes are occupied by bounded rational and socially influenced agents, as described in the previous paragraphs, can be assimilated to an agent-based model, defined as a "construct of an artificial environment where decision makers meet, eventually repeating certain interactions along recurring patterns that constitute a kind of collective decision process" ([9], p. 229). ABMs are representations of complex realities expressed in computer languages and therefore are able to be examined through computer simulations.

In the ABM used to study the performance of consensus formation by mutual influences in a network, a computational agent placed in the lattice of a communication network is a cell automata with a complex behaviour, combining errors of judgement with social influences from neighbouring members. Each automata interacts with neighbouring automata, exchanging information and social influences within predetermined communication networks and the degree of social influences (very much as in longitudinal social network analysis). This organisational domain satisfies the three conditions that make ABMs suitable for organisational research [9]: the structure matters (the performance of decision making by consensus varies across communication networks and is sensible to the degree of social influences); the bottom-up approach (the overall behaviour, the collective consensus around organisational change, arises from the interactions among individual agents); and the relevance of out-of-equilibrium results is satisfied because one of the performance measures is the number of iterations necessary to reach consensus, assimilated by the time spent on the process, with the longer the time the lower the present value of the pay-offs.

ABMs emerged naturally from computer sciences when the interest in calculating the values of variables was extended to represent the interactions among objects. Each object (a social actor in organisational research applications) entails a sequence of instructions on how to interact with others in the network (object-oriented programming), and the resulting interactions can be so large and complex that computer simulation is the only reasonable way of finding a meaningful solution. In this paper, computer simulation is not only a way of solving a computational problem to obtain the probability of achieving consensus on adoption (the alternative would be solving 2^{N-1} equations and unknowns, a complex problem with N large) but also a way of replicating the sequences of randomly determined mutual interactions with neighbours in the network until consensus is reached, which is how consensus is actually formed in the real world.

Figure 3. Simulation process diagram

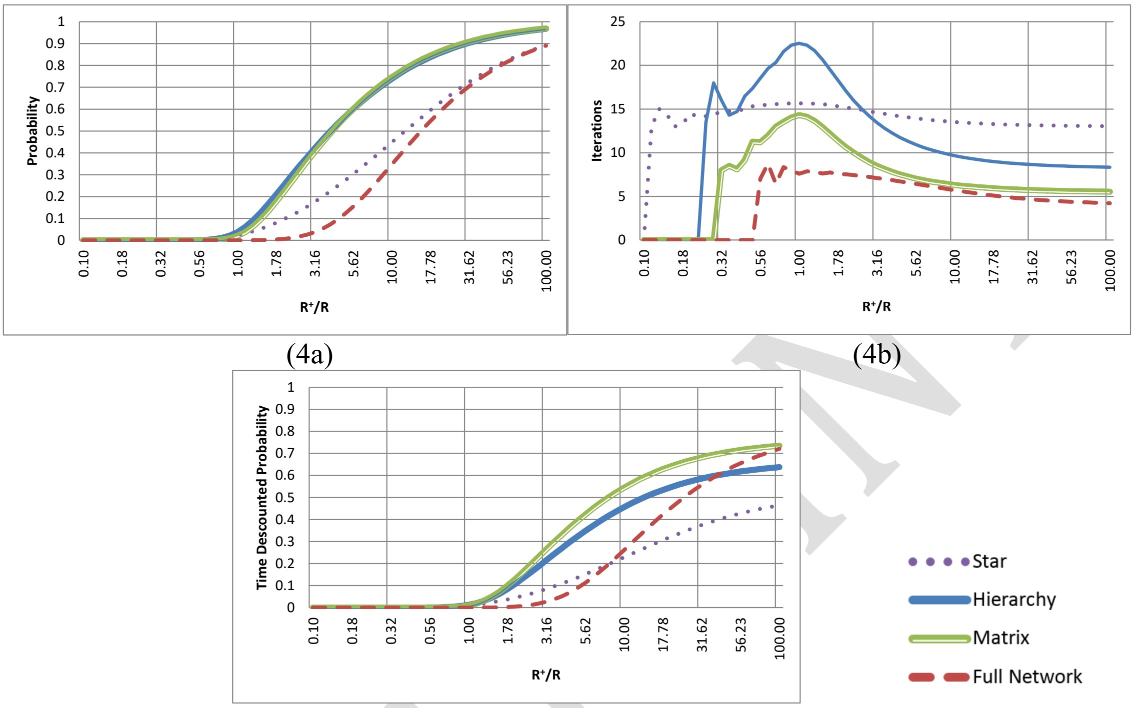


3. Simulation results

3.1. Comparison of performances among different communication networks

The base case is an organisation with 13 nodes, N=13, a parameter of social influences equal to one, δ=1, an interest rate of r=5% and a range of relative economic values attributed to the innovation, R^+/R, from 0.1 to 100. The communication networks considered are those shown in Figures 1. The results of the simulations for the base case are shown in Figure 4.

Figure 4. Probability of reaching a consensus in favour of adoption (4a), time to reach consensus (4b) and time-discounted probabilities of reaching a favourable consensus (4c): base case N=13, δ=1, r=5%.



(4a) (4b)

(4c)

From Figure 4a, the probability of achieving consensus in support of the adoption of innovations with R^+/R<1 is practically zero, that is, the probability of commission errors, Type II errors, is practically zero in the base scenario for all the communication networks. Figure 4a also shows that the consensus mechanism commits omission errors by rejecting innovations with an economic value R^+/R>1 with relatively high frequency, even when the value of the innovation is moderately high.

Given an economic value of the innovation, the probability of committing omission errors differs across communication networks. The networks with the lowest probability of committing omission errors are the hierarchy and the matrix. The probability is practically the same in the two networks, with the hierarchy slightly less fallible than the matrix for an R^*/R value slightly above 1. The probability of committing an omission error in the full network is much higher than in the hierarchy and the matrix. For example, a project with an economic value 3.5 times higher than the status quo has an equal probability of being adopted or rejected in a hierarchy and a probability of 5% of being consensually adopted in a full network.

From Figure 4b, it is apparent that, in all the networks, the largest number of iterations until consensus occurs in innovations with a relative economic value around one, in which differences with respect to the status quo are more difficult to discern. The time to reach consensus is practically invariant to the economic value of the innovation in the star (the hierarchy with a span of control of 13), while for the other networks the number of iterations decreases when R^{+}/R either increases for values of the ratio above 1 or decreases for values of the ratio lower than 1. The full network is the structure with the highest speed in reaching consensus in the case of adoption, followed by the matrix form, although the differences between the two disappear for high relative values of R^{+}/R. The differences in the time to reach consensus between the full network and the star, as well as the hierarchy and the matrix, remain constant for all the relevant values of R^{+}/R.

Figures 4a and 4b indicate that the choice of the communication network poses a trade-off: from the point of view of the probability of not incurring omission errors, the hierarchy is preferred to the full network, but from the point of view of the speed to reach a consensus favourable to adoption, the full network is preferred to the hierarchy. The matrix form has a similar probability of achieving a consensus in favour of adoption as the hierarchy but converges to consensus at a higher speed; combining probability and speed, the matrix outperforms the hierarchy in practically all the innovation values (Figure 4c).

3.2. Intensity of social influence effects

We now examine how the sensitivity of the results to different values of the parameter of social influences, from no social influence, $\delta=0$, to very high social influences, $\delta=\infty$. A value of $\delta = 0$, no social influence, implies a value of the probability in (1) equal to:

$$p^{ji} = \frac{R^{+}}{R + R^{+}} \qquad (2)$$

The probability of supporting adoption depends only on the relative value of the innovation, so it is the same for all the individuals in the network and constant across iterations. If the individuals in each node of the network were unbounded rational, an innovation with $R^+ > (<) R$ would immediately be adopted (rejected). Bounded rationality as assumed here means that, faced with an innovation of value R^+ two times the value of R, the probability of forming a favourable opinion by an individual in the network is 2/3 and a probability of forming an opinion contrary to adoption of 1/3 (probability of an omission or Type I error because $R^+>R$). If $R^+<R$, for example R^+ is half the value of R, then the probability of making a commission error, (a Type II error of supporting the adopting of an innovation that destroys value) is 1/3. For the particular case of equation (2), the probability of committing omission and commission errors is always less than 1/2. Equations (1) and (2) could be extended to allow for different degrees of rationality (expertise) with R^+/R to a positive, but not necessarily equal to one, power parameter.

Very large values of δ, on the other hand, are representative of a culture with strong social influences (the opinions of others weigh highly in the formation of an opinion by each member of the group). When the value of δ tends to infinity, equation (1) takes the form:

$$p^{ji} = \frac{b_t^j R^+}{a_t^i R + b_t^j R^+} \qquad (3)$$

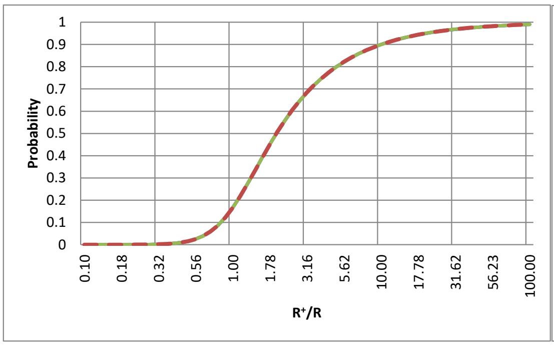
The probability of forming a favourable opinion on adoption now depends only on the relative number of neighbours with similar opinions, weighted by the value attributed to the innovation (the conviction of neighbours when exerting social influences on others increases with the relative value attributed to the innovation). At the time of the discovery, the number of favourable opinions in the group of influence is zero, b=0. If the group of individuals in the circle of influence of individual i, who supports the status quo, is a positive number, $a>0$, then the denominator in (3) takes the value of infinity (recall that b=0). Now, the probability of j convincing i to form a favourable opinion is equal to zero for any value of R^+. The only chance that an innovation can advance beyond the first filter when δ tends to infinity is that the perturbation occurs in an isolated node (the size of the group of influence is zero).

The simulation results provide more detailed evidence on the direction and magnitude of changes in the performance of consensus formation as a function of different degrees of social influences, and how the effect of social influences can differ across communication networks; see Figures 5 and 6.

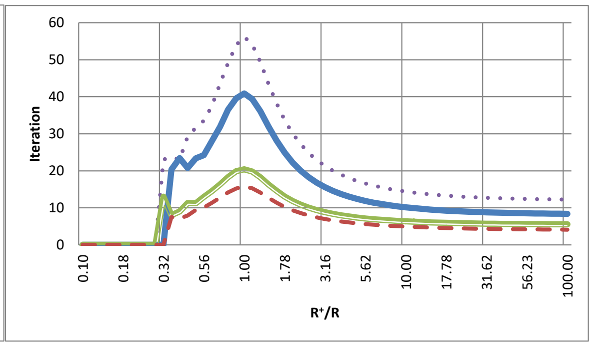
As expected, δ=0 implies that the probability of adopting an innovation of a given economic value is the same for all communication networks; see Figure 4a. The probability of making commission errors continues to be very small, while the probability of making omission errors is positive but decreasing with the relative economic value of innovation. Comparing Figure 4a with Figure 5a, we observe that positive social influences, δ=1, lower the probability of reaching consensus on adoption for all economic values of the innovation, compared with the probability when social influences are absent, δ=0. The increment in the probability of committing an omission error under social influences is higher in the full network and lower in the hierarchy and the matrix: the probability of committing an omission error in the full network for a relative economic value of the innovation equal to 3.5 changes from 95% when δ=1 (Figure 4a) to 30% when δ=0 (Figure 5a). However, the presence of social influences lowers the probability of committing commission errors in all the communication networks, although this probability is also low without them.

The full network is again the one that takes the lowest number of iterations to reach a consensus in favour of adoption, followed closely by the matrix form; Figure 5b. Since the probability of achieving a consensus favourable to adoption is the same across communication networks, the time to reach consensus should determine the ranking of the overall performance (Figure 5c).

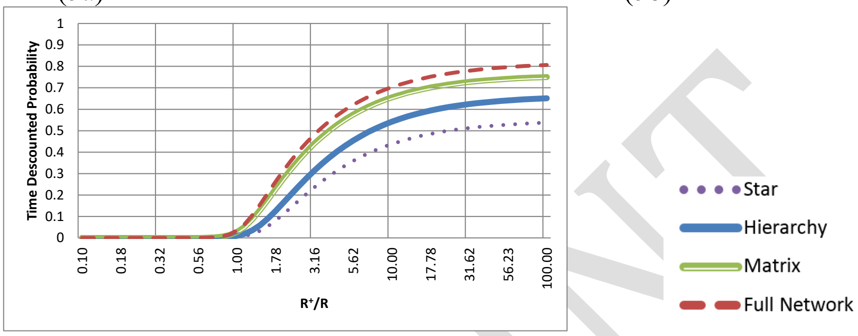
Figure 5. Probability of reaching a consensus favourable to adoption (5a), time to reach consensus (5b) and time-discounted probabilities of reaching a favourable consensus (5c): N=13, r=5% and δ=0.



(5a)



(5b)

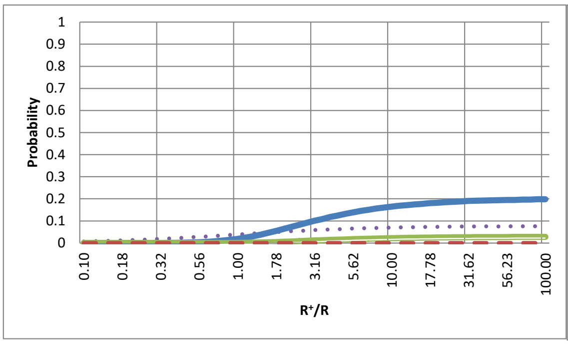


(5c)

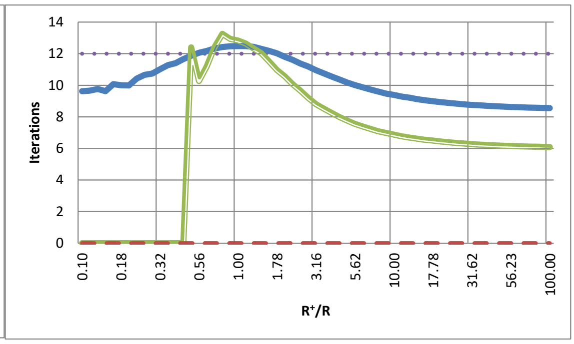
When δ=∞, equation (3), the opinions of neighbours dominate the own opinion formation over intended rationality. Figure 6a confirms the intuitions from equation (3) that, under strong social influences, the probability of reaching a consensus in favour of innovation adoption and therefore a consensus on change is very low for all the communication structures and practically zero for the full network. These low probabilities occur even when the gains from adoption can be very high compared with those of the status quo. When the social influences are strong, the probability of committing omission errors by rejecting innovations with high economic value can be quite high. The reason is that, with high social influences, the pressure from those in favour of the status quo prevents the organisation from undertaking any innovation-induced change. The hierarchy appears to be better protected from making omission errors with a high δ.

The matrix converges to consensus faster than the hierarchy, especially for innovations with relatively high economic value; see Figure 6b. In terms of time-discounted probability, the hierarchy continues with performance superior to that of the matrix form; see Figure 6c. The full network always rejects adoption for all economic values.

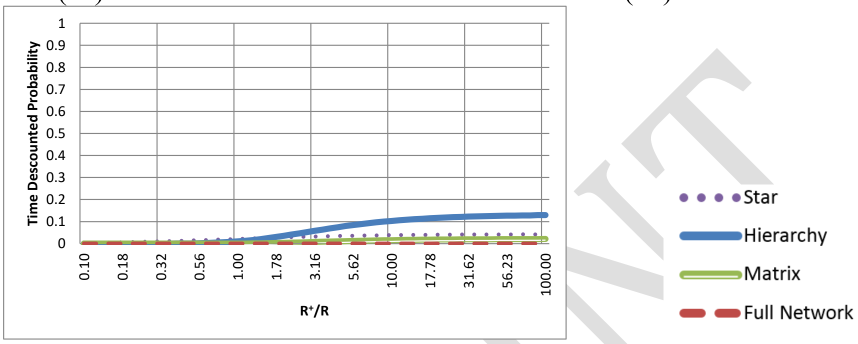
Figure 6. Probability of successful adoption (6a), time to reach consensus (6b) and time-discounted probabilities of reaching a favourable consensus (6c): N=13, r=5% and δ=∞.



(6a)



(6b)



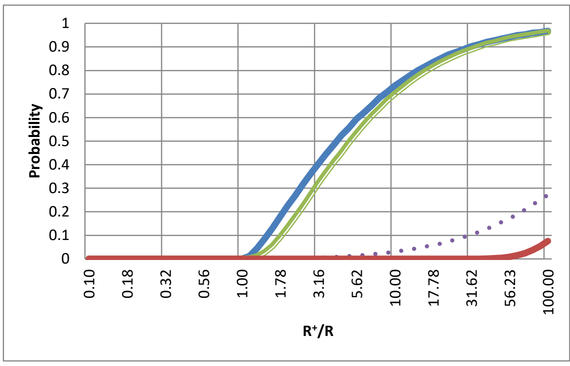
(6c)

3.3 Organisation size

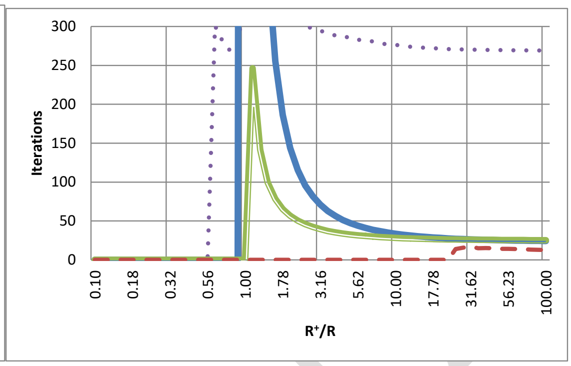
We now compare the performances in networks of different sizes. In a network of 270 nodes, the probability of reaching a consensus in favour of the adoption of innovations when R^+/R<1, a commission error, is practically zero; see Figure 7a. For innovations with R^+/R>, the likelihood of reaching a consensus in favour of adoption is almost independent of the size of the network, except in full networks, in which the probability of adoption decreases with the size of the network (Figures 4a and 7a). Then, the likelihood of committing omission errors in full networks increases with size.

The number of iterations needed to reach a consensus in favour of adoption increases with the size of the network in all the communication network structures (Figure 7b). In the hierarchy and the matrix, in which increasing the size of the network does not increase substantially the omission errors, the time needed to reach consensus increases considerably with the size of the network. In the large network of N=270, the hierarchy shows a lower probability of making omission errors than the matrix (Figure 7a), but the time to reach consensus in the matrix is substantially lower than in the hierarchy, especially for innovations with moderate value (Figure 7b). The choice between hierarchy and network will have to weigh the lower probability of making omission errors in the hierarchy against the shorter time to reach consensus in the matrix.

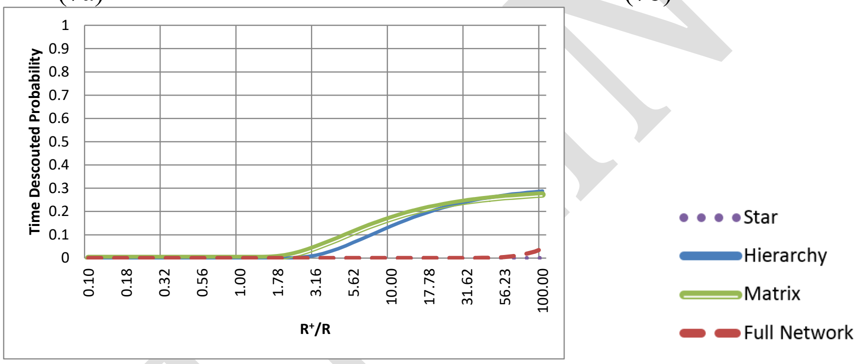
Figure 7. Probability of successful adoption (7a), time to reach consensus (7b) and time-discounted probabilities of reaching a favourable consensus (7c): N=270, r=5% and δ=1.



(7a)



(7b)



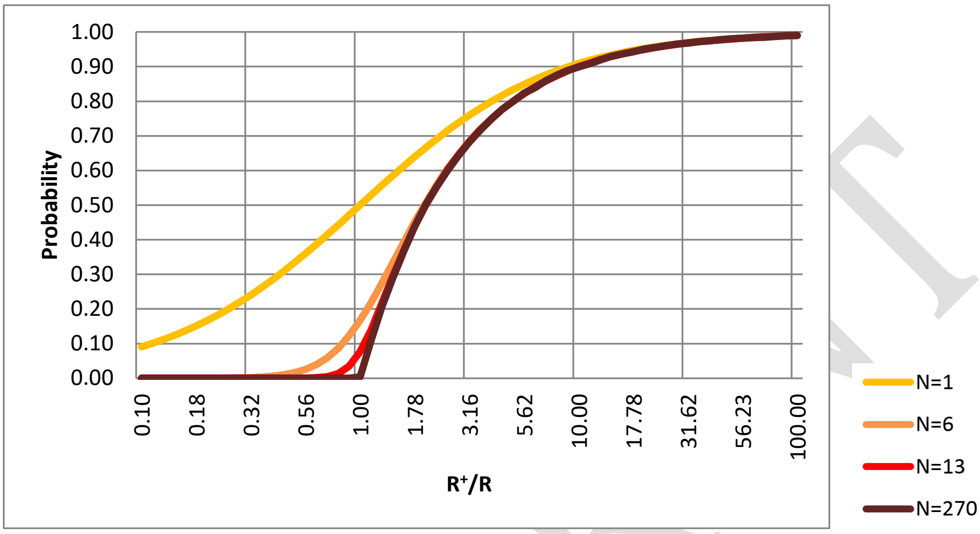
(7c)

Figure 8 shows the probabilities of reaching a consensus in favour of adoption (vertical axis) for every relative economic value of the innovation (horizontal axis), in hierarchy networks of sizes N=1, 6, 13 and 270. The social influence parameter is set equal to zero, δ=0, to make the results more comparable with those of a single decision maker, N=1, for whom social pressures are non-existent. The results indicate that a larger network size lowers the probability of committing commission errors and is practically zero for values of N>13. A group consensus among bounded rational individuals reduces the probability of committing commission errors compared with the probability of a single bounded rational decision.

As for the likelihood of committing omission errors, Figure 8 shows that this probability is lower for the bounded rational single decision maker than for groups making decisions by consensus. However, the size of the group is relevant as a determinant of the probability of omission and commission errors for relative values of the innovation around one and for group sizes up to

N=13. As the relative economic value increases, the differences in the probability of committing omission errors between a single decision maker and a group consensus disappear, even for groups of a small size.

Figure 8. Probabilities of consensus on adoption in hierarchy networks with different number of nodes, N (δ=0)



4. Discussion of the results and related literature

The results from the computer simulations confirm that the fallibility of consensus-based decisions, that is, the possibility of committing commission and omission errors, depends on both the fallibility of individual members and the organisational structure, composed of the communication network and the degree of social influences, in which such consensus formation is implemented. Computer simulations also show that the organisational structure matters in determining the time to reach consensus and therefore the present expected value of the innovation adopted. Table 1 summarises the main findings on the effects of organisational structure variables in the performance of consensus-based decision-making (fallibility and time to reach consensus).

Table 1 poses some trade-offs faced in organisation design decisions. One of these trade-offs is between fallibility, in terms of the probability of committing an omission error, which is lowest in the hierarchy and the matrix and higher in the full network, and the time to reach consensus, which is lower in the full network than in the others. The other trade-off is posed by the size of the network. A larger size of the network lowers the probability of committing commission errors but at the expense of increasing the time to reach consensus. These trade-offs are more relevant to relative values of the innovation that are not too different from one, for which it is more difficult to compare the economic value of the innovation with that of the status quo; when the relative value of the innovation is high, many of the differences in the probability of committing errors from differences in the parameters of the model vanish.

Table 1. Summary of the effects of the type and size of the network and the intensity of social influences in the performance of consensus-based decision making for relative values of the innovation close to one.

	Probability of Adoption		**Time to consensus**
	Commission error	Omission error	
Network			
Hierarchy	=	=	=
Matrix	=	+	-
Full Network	=	+	-
Size	-	-	+
Social Influence	-	+	+

In the network types, the sign + (-) indicates that the value of the performance variable is comparatively higher (lower) than the performance of the hierarchy.

The simulation results also confirm that consensus-based decisions made through mutual adjustments, as modelled in this paper, reduce the probability of commission errors, adopting value-destroying innovations in our case, compared with the probability of commission errors being made by a single equally bounded rational decision maker. The advantage of consensus-based decision making over other collective decision-making mechanisms, including authority-based ones, in terms of a lower probability of commission errors being made by fallible individuals, is well known [22]. What we undertake in this paper that is new to the literature is to examine the sensitivity of the general result to the type and size of the communication network and the degree of social influences. We find that the results in terms of a low probability of commission errors in consensus decisions hold for all communication networks but decrease with the size of the network and with the degree of social influences.

However, consensus-based decisions also increase the probability of omission errors, rejecting the adoption of value-creating innovations, compared with the probability of omission errors being made by a single equally bounded rational decision maker. This probability increases with the size of the network and with the degree of social influences, but decreases rapidly with the relative economic value of the innovation when R^+/R>1 and varies across communication networks. When only fallibility matters, the hierarchy and the matrix perform better than the full network in terms of a lower probability of committing omission errors. If the priority is to shorten the time to reach consensus, then the full network is preferred. The trade-off between the two performance measures has already been highlighted by the information in Table 1.

Differences in fallibility across communication networks occur only when social influences matter. If δ=0, then the individual fallibility depends only on the relative value of innovations, which is the same for all individuals, the probabilities of commission and omission errors are the same for all the networks and the only differences among them occur in the time until performance, for which the full network outperforms the others (the shortest time to reach consensus). As social influences become positive and increase, the effect on the individual fallibility, a sign of the derivative of the probability in (1) with respect to δ is undetermined since it depends on the values of *a* and *b* (neighbours supporting the adoption or not). The simulations confirm that more intense social influences increase the omission errors and bias an organisation towards continuing with the status quo (a lower probability of change). The speed of convergence (the iterations needed to reach a consensus) is practically unaltered by the intensity of social influences.

The technical explanation for these results concerning the effect of the intensity of social influences on a group's fallibility has to do with the connectivity of network types. A higher average connectivity in the network implies that, in any iteration, more individuals have an opportunity to interact with their neighbours in each round of information exchange and mutual influence, but, at the same time, higher connectivity implies that, for a given degree of social influences, each node will have more neighbours whose influences will affect the formation of the node's own opinion. The average connectivity of the full network is higher than the average connectivity of the hierarchy and the matrix for a given total network size. The simulations show, as expected, that the full network tends to reach consensus faster than other communication networks, benefited by the possibility of interacting with more neighbours, but, at the same time, higher connectivity penalises the full network with the effect of the weight of the opinion of others in own opinion formation.

When the social influences are high, the relative economic value of the innovation has little effect on the outcome from information exchange, especially when the value is modest. In the first round of the consensus formation process, when the person in the perturbed node decides whether to convince the others to accept the innovation or to continue with the status quo, all the neighbours will exert social pressure in favour of the status quo. In the full network, all the nodes have similar connectivity that in turn is higher on average than the connectivity in the other networks. In the full network, all the nodes have neighbours whose opinion in favour of the status quo influences the opinion formation of the perturbed node. If the intensity of the social influences is very high, then the person in the full network who first knows about the innovation will form an opinion in favour of rejecting the innovation with a probability close to one; the innovation will be ignored in the first round and there will be no change to be evaluated by others.

In the hierarchy, the nodes at the end of the tree have the connectivity of 1. If the innovation appears for the first time in someone connected with these nodes, then there will be individuals who are influenced by the conversations with the person in this node, who will have zero supporters of the status quo in his or her group of influence; he or she will be unaffected by the social influences and the decision will be based only on the relative value of the innovation. In these cases, the probability that the informed neighbour will also support adoption can be positive, even when the parameter that captures the intensity of the social influences is very high. The final probability of reaching a consensus in favour of adoption, however, will be low, even for high relative economic values, because in its calculation there is the likelihood that the innovation will appear for the first time in the nodes connected with those that have a connectivity of 1 and their first interaction is with each other.

The different increases in average connectivity as the size of the network increases across communication network types also explain the different effects on fallibility and time to reach consensus of a larger number of nodes across networks. In full networks, the average connectivity is N-1, so it increases directly with the number of nodes. In the hierarchy and the matrix, connectivity only increases moderately with the size of the network. A larger size strongly penalises the probability that consensus will converge on the adoption of innovations because the greater connectivity directly increases the number of supporters of the status quo in the group of influence of the node, where the consensus process begins. On the other hand, a larger network also has comparative advantages, since the higher connectivity increases the number of nodes with whom to have conversations in each round.

In the full network, the time-discounted probability of adoption by consensus decreases with the size of the network and becomes close to zero for moderate sizes, even when the economic value of the innovation is relatively high. In the hierarchy and matrix forms, with lower average connectivity, the larger size of the network substantially increases the time to reach consensus, especially with relatively low economic value of the innovation, but the penalty in the probability of achieving consensus on adoption, especially in innovations with high relative economic values, is comparatively small. Overall, in relatively large organisations, the hierarchy and the matrix demonstrate better performance in terms of the time-discounted probability of reaching consensus on the decision to adopt the innovation, especially with innovations of moderate relative economic value.

4.1. Relationship with organisational research

Bounded rationality and social influences are at the core of the organisational approach to studying social behaviour and institutions. In this section, we refer to connections between analyses of the performance of consensus-based decisions in collective actions under different organisational structures, presented above, and other topics of organisational research. In particular, we draw implications from our analysis on the balance of exploration and exploitation in organisations; on the trade-offs between insulation versus socialisation in organisational design; and on the speed of diffusion of innovations in populations of potential adopters.

Exploration versus exploitation

It is well established in organisational research that inertia, experience and preferences in favour of uncertainty reduction push organisations to continue with the status quo at the cost of the scarifying exploration of new ideas that could turn into profitable innovations. On the contrary, organisations that push to continue exploration for innovation will shorten the exploitation times of the established technologies beyond what would be considered reasonable [44,45,46,47,48]. The research question is then how to balance exploitation and exploration optimally [49,50] and which instruments should be used for this purpose.

The simulation results presented in this paper confirm that the organisational structure matters in the balance between exploitation and exploration [51,15,52]. In our analysis, the time needed to reach consensus on adopting an innovation and the likelihood (lower) of the outcome are indicators of the exploitation time of the technologies and practices proper of the status quo. This is so because we assume that consensus formation does not interrupt the operating activities of the organisation, as would be the case with consensus formation in committees.

The simulation results suggest that the hierarchy and matrix networks perform better than the full network in terms of the probability of reaching consensus but take a longer time to reach it, while in the full network the situation is reversed. If only time to reach consensus matters, as is the case in networks with no social influences, organisations that weight exploitation more heavily may choose to implement consensus formation in hierarchies or matrix networks, while those that place greater weight on exploration may prefer full networks. When social influences affect the probability of reaching consensus on adoption differently in one network from the other, then the time discounted probability of adoption can be useful to find the right balance between exploitation and exploration.

Isolation or socialisation

Social influences appear as a homogenisation force from which groups often try to protect themselves. March [50] notes that the international community of researchers is fragmented geographically, linguistically and culturally in relatively autonomous academic communities, which facilitates a certain resistance to the homogenising tendencies of the dominant scholarly groups. Fragmentation of large groups in communities slows the consolidation of a dominant paradigm and stimulates both the persistence of new ideas and experimentation. The so-called "small world", in which a community of agents is structured around well-defined groups with few interconnections among them, contributes to preserving the range of different forms of expertise within the whole community [53,54,55], while smaller and more isolated groups help to generate a shared identity and to exchange information, increasing reciprocity and trust [56].

The intensity of social influences as one element of the opinion formation process pushes the individuals in the group towards consensus around one opinion; the intensity of social influences is then a homogenising force. What our simulation analysis shows is that the time to reach consensus, and therefore the period when differences in opinion can persist among group members, will differ depending on the connectivity of the network in which the social influences operate. The predictions from the outset are not obvious. On the one hand, networks with low connectivity, and therefore with isolated nodes, protect these nodes from the homogenising force of the social influences. On the other hand, this deprives the isolated nodes from the benefits of socialisation, this time in the form of participating in information exchanges about the value of the innovation with a larger number of neighbours.

In the cases studied in this paper, the balance of this trade-off turns out to vary depending on the relevant measure of performance. Greater connectivity and the possibility of exchanging information with a larger number of neighbours appear in the form of a higher likelihood of reaching a consensus supporting the innovations but also a need for more time to reach consensus.

Diffusion of innovations

The adoption of innovations over time among groups of potential adopters and the time path in the diffusion of innovations has been traditionally modelled as a process whereby non-adopters make probabilistic choices about adoption or otherwise at a given moment of time [57,58]. In most of these models, the adoption of an innovation means the purchase of a new and durable product by a potential buyer, while in our model of consensus formation, the adoption decision is made by the whole group; the process towards consensus will reflect who in the group supports the adoption of the innovation and who supports the status quo at every moment of time, but the decision on whether to adopt the innovation or not will be postponed until consensus is reached. Broader approaches to the study of the diffusion of innovations inspired by Rogers [59], which extend the scope of the diffusion to opinion formation around ideas, policies or cultural values, could be accommodated in our framework.

Another distinct feature of conventional diffusion models is that they ignore the structure of the network that connects the potential adopters. The common assumption is that the influence of previous adopters on the adoption decision by those who have not yet adopted comes from all adopters, not from the neighbours of a hypothetical network, as we suggest here. Finally, in conventional diffusion of innovation models, the only influences are those exerted by previous adopters on non-adopters; the social influence of the non-adopters defending the status quo has not been considered. In our model of consensus formation, the social influences are exerted in both directions. In our framework, the assumptions implicit in the diffusion of innovation model, no influence of non-adopters on the adoption decision, would change (1) to:

$$p_t^{j,i} = \frac{\left(1+\delta N_t\right)R^+}{\left(1+\delta N_t\right)R^+ + R} \tag{4}$$

Where N_t, the number of previous adopters in iteration or time period t, replaces b_t in (1) and a_t=0 because there is no social influence from non-adopters supporting the status quo. When the innovation appears for the first time N_t=0 and the probability of supporting adoption is $p_0^{j,i} = \frac{R^+}{R+R^+}$, increasing with the relative value of the innovation, similar to the parameter "*p*" in Bass's model [57]. As the number of previous adopters N_t increases, the probability of adoption by a non-adopter also increases; δ is the weight of the influence of previous adopters on the probability of new ones, similar to the imitation parameter "*q*" in Bass [57].

Kuandykov and Sokolov [60] extend the traditional diffusion models to account for the structure of the network in which diffusion takes place, so in this respect our model is similar to theirs. The difference is that our equation (1) is more general than equation (4), used in other papers, since it is not restricted to innovations with $R^+ > R$, and we take into account the pressure of existing technologies and practices in defending the status quo. The consequence of these differences is that the diffusion of the innovation that postulates probability (4) of adoption by non-adopters predicts that all potential adopters will adopt with probability one (no fallibility), while in the general case this probability is lower than one (the status quo prevails).

Conclusions

The organisational approach to studying the functioning of complex societies is built around two features of human behaviour, bounded rationality and the intensity of social influences. Organisational research focuses on how organisational structures, that is, the allocation of decision-making power, communication networks and the intensity of influences, explain certain collective behaviour and on how to change them to improve social performance. The complexities posed by these tasks are well acknowledged, so a diversity of research methodologies are needed, including complex mathematical models, empirical studies and computer simulations in symbolic laboratories.

This paper uses computer simulations to study the performance of consensus-based decision making in groups under different communication networks and degrees of social influences, when group members form their opinions about supporting the proposal for change or not, combining intended rationality and social influences at the same time. The relevance of studying the performance of consensus-based decision making, as proposed in this paper, is justified by the advance of production systems and work organisations that are intensive in knowledge and information sharing among peers, supported by communication networks that facilitate exchanges, and by the diversity of empirical and theoretical research concerning the potential costs and benefits of consensus over other mechanisms of collective decision making.

The results of the paper confirm that the organisational structure that aggregates individual fallibility from bounded rationality to collective fallibility matters for performance and, therefore, that structure is a design tool at the disposal of managers to improve organisational performance. The consensus formation examined in the paper considers a collective action supported by a communication network such that in each node, perturbations occur randomly in the form of new projects, ideas or policies to which the group must respond with a decision to accept or reject them in a unanimous way. Within this context, the paper confirms the advantage of consensus-based decision making when the main concern is to reduce the probability of making costly commission errors in organisations, but now extends it to consensus in communication networks. We also find that the probability of making omission errors can differ substantially across different communication networks but that the prescription in the choice of one network or the other is complicated by the fact that the networks with a lower probability of committing omission errors are also those that take a longer time to reach consensus. Finally, the simulation results also show that social influences can affect the performance of consensus-based decision making differently in hierarchy and matrix networks compared with full networks.

The paper can be extended to compare the performance of consensus-based decision making with the performance of other collective decision-making mechanisms, such as authority-based decision making. Another natural extension is to situations in which the exchange of information among organisational members includes the exchange of knowledge, so consensus formation may affect the quality of the decisions; in this paper, the value of the innovation is determined exogenously, while in models that allow for learning as part of the information exchange process, the value could be endogenous.

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